PARTIAL REMOVAL OF CORRELATED NOISE IN THERMAL IMAGERY

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ABSTRACT

Correlated noise occurs in many imaging systems such as scanners and push-broom imagers. The sources of correlated noise can be from the detectors, pre-amplifiers and sampling circuits. Correlated noise appears as streaking along the scan direction of a scanner or in the along track direction of a push-broom imager. We have developed algorithms to simulate correlated noise and pre-filter to reduce the amount of streaking while not destroying the scene content.

The pre-filter in the Fourier domain consists of the product of two filters. One filter models the correlated noise spectrum, the other is a windowing function e.g. Gaussian or Hanning window with variable width to block high frequency noise away from the origin of the Fourier Transform of the image data. We have optimized the filter parameters for various scenes and find improvements of the RMS error of the original minus the pre-filtered noisy image.

Keywords:

1/f Noise, Image Quality, Electro-Optics, System Simulation

Introduction

Airborne multi-spectral scanners and push broom systems often contain substantial amounts of correlated noise leading to striping visible to an observer. In the past striping has been removed using Fourier analysis techniques, e.g. wedge block filters have been used to improve the qualitative appearance of imagery (Lillesand and Kiefer, 1994). When Fourier analysis was deemed too computationally expensive, simpler spatial filtering methods have been developed (Crippen, 1989).

Source of Correlated Noise in Imaging Systems

- Occurs in scanners and push-broom imagers
- Sources are: detectors, pre-amplifiers and sampling circuits
- Power-law correlated noise has spectrum $N(f) = f^\alpha$ where the slope α ranges typically between -0.25 and -2
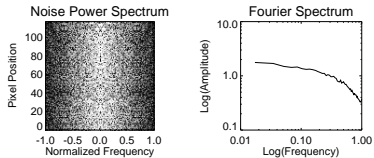
Example:

Figure 1: Measured correlated noise of a MCT camera

MCT long wave camera (Inframetrics 600 MCT)

Modeling of Correlated Noise for an Infrared Imager

Steps:

1. Generate uncorrelated (Gaussian) noise signal $s_1(t_k)$ for $x = 1, \ldots, N_x$ samples
2. Compute "Fast Fourier Transform" (FFT) of $s_1(t_k)$ is $S_1(f_x)$
3. Multiply $S_1(f_x)$ with filter response function $F(f_x)$
4. Correlated noise signal:

$$s_2(t_k) = s_1(t_k) \otimes f(t_k) = FFT^{-1}[S_1(f_x)F(f_x)], \quad x = 1, \ldots, N_x \quad (1)$$

where $\otimes$ is a symbol for the discrete convolution.

Noise signal for an imaging system:

$$N_{noise}(x,y) = N_{Gauss}(x,y) + N_{cor}(x,y;\alpha)$$
$$= \frac{R_1(x,y)}{STDEV(R_1(x,y))}\frac{1}{SNR_{Gauss}} + FFT^{-1}\left[FFT\left[\frac{R_2(x,y)}{STDEV(R_2(x,y))}\frac{1}{SNR_{cor}}\right]f_x^\alpha\right], \quad (2)$$

where R_1 and R_2 are white Gaussian random signals and $STDEV$ denotes the standard deviation. For 1/f noise we have $\alpha = -1$.

Algorithm to Partially Remove Correlated Noise

Goal:

Reduce the amount of streaking while minimizing changes of the scene content.

Sensor characteristics:

- Scanner: correlated noise in the cross track direction
- Push-broom: correlated noise in the along track direction
- 2-D array: correlated noise in successive frames (not considered here)

Observations:

- Filtering process need be carried out only on the frequency axis where the correlated noise appears (e.g. f_x in Figure 4)

- Inverse transformed image will have much less correlated noise contamination (Figure 5)
- No filtering performed near the "origin" (location of zero spatial frequency) to preserve scene information
- Filtering the region near the origin of the transform image will alter the radiometry of the original image

General filter:

$$F(f_x, f_y) = 1 - F_1(f_x)F_2(f_y), \quad x = 1, \ldots, N_x; \ y = 1, \ldots, N_y, \quad (3)$$

where $F_2(f_y \neq 0, 0) = f_y^\alpha$ and $F_2(f_y = 0, 0) = -1$ represents a correction of the correlated noise and α is the slope in a Log-Log plot of the noise spectrum.

(A) Gaussian Filter (used primarily):

$$F_1(f_x; \beta, \sigma) = (1 - \beta)\exp\left[-\left(\frac{f_x}{\sigma}\right)^2\right] + \beta \quad (4)$$

as a weighting function which preserves spectral components near the origin with a standard deviation of σ and offset β which have to be chosen for a particular scene.

Notation:

Filter $F_{PRCNF}(f_x, f_y; \alpha, \beta, \sigma)$, where $PRCNF$ stands for the "Partial Removal of Correlated Noise Filter"

(B) Modified Hanning window function:

$$F_1(f_x; \beta, \gamma) = \left[(\beta - 1)\cos\left(\frac{2\pi j}{N_x - 1}\right) + \beta\right]^\gamma \quad (5)$$

where β is an offset and γ is an exponent to change the width of the peak.

Notes:

- The Hanning window is defined for $\beta = 0.5$ and $\gamma = 1$
- The Hamming window is defined for $\beta = 0.54$ and $\gamma = 1$

OTF and PSF Degradation Effects

Observation:

The partial removal of correlated noise degrades the overall "Optical Transfer Function" (OTF) and "Point Spread Function" (PSF) of the optical system, e.g.:

$$OTF_{tot}(f_x, f_y) = OTF_{Atmosphere}(f_x, f_y)OTF_{Telescope}(f_x, f_y)OTF_{Motion}(f_x, f_y)\cdots$$
$$OTF_{Pixel}(f_x, f_y)OTF_{Electronics}(f_x, f_y)OTF_{PRCNF}(f_x, f_y; \alpha, \beta, \sigma), \quad (6)$$

where $PRCNF$ stands for the "Partial Removal of Correlated Noise Filter".

Note:

This does not necessarily mean that the effective image content and radiometric accuracy are degraded. In uniform scenes the "striping" effect can be significantly reduced using the PRCNF method.

Error Metric:

Root Mean Square Error (RMSE) of the difference between the "original" image (with no noise) and the PRCNF filtered noisy image.

Heterogeneous Scenes:

the use of the PRCNF will blur the image somewhat

Example:

OTF of the PRCNF with $\alpha = -1$, $\beta = 0.1$ and $\sigma = 0.1 * N_x$.

Optimizing Method

Question:

How much correlated noise can be removed before the scene content is affected?

Assumptions:

- Let $I_{ref}(x,y)$ be a reference image of the scene of interest with no correlated noise (e.g. taken by a MWIR imager).
- Let $N_{noise}(x,y) = N_{Gauss}(x,y) + N_{cor}(x,y;\alpha)$ (eq. (2)) be a noise image taken by the LWIR sensor without a scene (e.g. closed aperture, blackbody of similar brightness temperature as the scene).

Steps:

1. Let $I_1(x,y) = I_{ref}(x,y) + N_{noise}(x,y)$ be a "simulated" scene with both noises (band limited white and correlated) added and filter it with $F_{PRCNF}(f_x, f_y; \alpha, \beta, \sigma)$ to result in:

$$I_2(x,y) = FFT^{-1}[I_1(f_x, f_y)F_{PRCNF}(f_x, f_y; \alpha, \beta, \sigma)]$$

2. Compute the RMSE of $(I_2(x,y) - I_{ref}(x,y))$ and select the optimum PRCNF parameters: β_{opt}, σ_{opt} when $RMSE(\beta_{opt}, \sigma_{opt}) = Min$

3. Filter the true scene image I_3 which contains similar both kinds of noise similar to the noise image $N_{noise}(x,y)$:

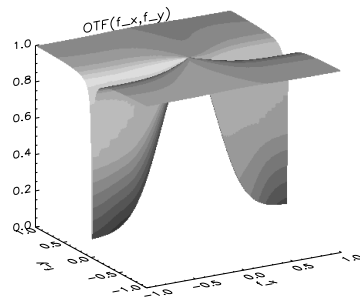$$I_4(x,y) = FFT^{-1}[I_3(f_x, f_y)F_{PRCNF}(f_x, f_y; \alpha, \beta_{opt}, \sigma_{opt})]$$

Figure 2: OTF of the "Partial Removal of Correlated Noise Filter"

Highly structured scenes:

the optimum filter will remove less correlated noise because the scene content would be too much degraded

Uniform scenes:

correlated noise reduced (e.g. night time LWIR)

Mixed scenes:

Adaptive filter which changes the filter parameters according to scene content (not pursued here)

Results:

The optimization of the proposed filter is graphed in Figure 6 using the following definitions:

$$RMSE1 = RMSE(I_{ref}(x,y) - FFT^{-1}[I_{ref}(f_x, f_y)F_{PRCNF}(f_x, f_y; \alpha, \beta_{opt}, \sigma_{opt})])$$
$$RMSE2 = RMSE(I_2(x,y) - I_{ref}(x,y))$$

and

$$Ratio_{STDEV} = \frac{STEDEV(I_2(x,y))}{STDEV(I_1(x,y))}.$$

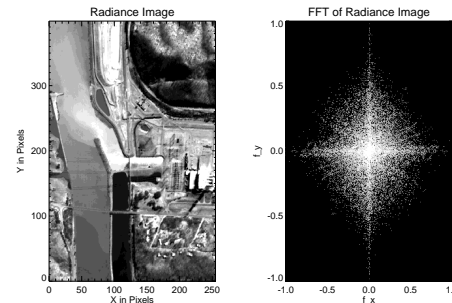Note we plot $RMSE1$, $RMSE2$ and $Ratio_{STDEV}$ in units of K.
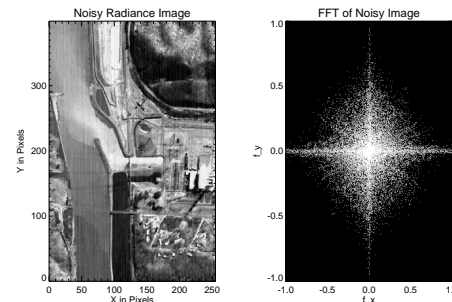
Figure 3: Noise free image.

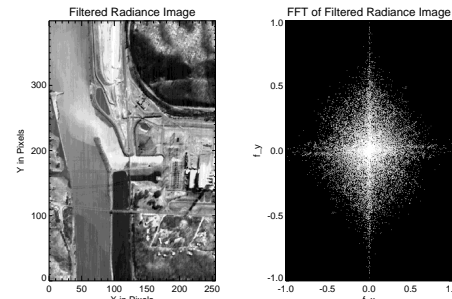Figure 4: Image with partial correlated noise ($SNR_{cor} = 50$ and $SNR_{Gauss} = 500$).

Figure 5: Partial removed correlated noise.

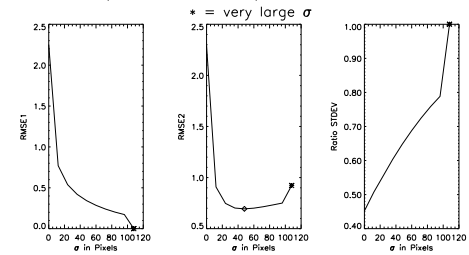### Optimum RMSE2_opt=0.693836 at σ=48
* = very large σ

Figure 6: Optimization result for the images shown in Figures 3-5

Subtracting Linear Trends

Question:

Can we reduce correlated noise using black body temperature measurements?

1. Measure at time T_a and pixel $y_a = T_a/\Delta T$, where ΔT is the time between samples)
2. Measure after a scan (at time T_b and pixel y_b)
3. Slope correction:

$$I_{slope}(x,y) = I_1(x,y) - \left[I_1(x,y_a) + \frac{I_1(x,y_b) - I_1(x,y_a)}{y_b - y_a}y\right] \quad (7)$$

4. The slope corrected image $I_{slope}(x,y)$ is then filtered using the $PRCNF$ method.

Example:

Simulation Result:

- A scanner was simulated by generating 256 realizations of correlated noise with 256 samples each.
- Assuming $y_a = 0$ and $y_b = 255$ we computed the ratio:

$$Ratio_{STDEV} = \frac{\sigma(I_{slope})}{\sigma(I_{noise})},$$

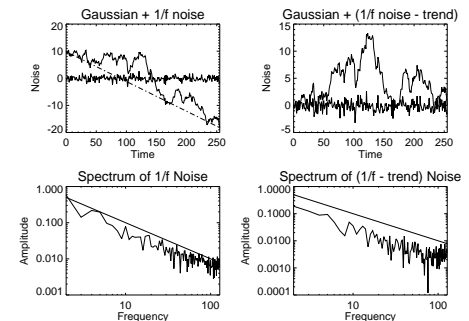for a noise with $SNR_{cor} = 50$ and $SNR_{Gauss} = 500$.

Figure 7: Simulation of linear trend removal. Note amplitude of noise is reduced.

- $Mean(Ratio_{STDEV}) = 0.81$ with standard deviation $STDEV(Ratio_{STDEV}) = 0.248 \Rightarrow$ thus an improvement in SNR is obtained when the linear trend is removed
- Note however that it possible occasionally that the $Ratio_{STDEV}$ is above unity, e.g. the noise measurements have both similar large magnitudes but the noise mean is close to zero.
- The slope correction fails if one waits too long before and after image acquisition for the noise measurements (e.g. $T_b - T_a >> N_y \Delta T$).

Bottom line:

The observed improvement in the previous image was surprisingly small (0.6754 K vs 0.6938 K) for the case $y_a = 0$ and $y_b = N_y = 255$.

Conclusions

- A method has been developed which reduces the visually disturbing effect of correlated noise in long wave thermal imagery while preserving the image resolution and radiometric accuracy.
- The PRCNF method can be optimized for a given scene if an almost noise free image in another thermal channel (e.g. MWIR) is available, and a noise image in the channel of interest.